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Teaching and learning based optimization algorithm as a tool for maximum power point determination for bifacial PV

***Abstract**. In photovoltaic systems it has been always a challenge to determine the methodology for calculation of the maximum power point (MPP) for given system, location and atmospheric conditions. Therefore, many optimization methods are in use as well as different photovoltaic cell circuit presentations. In this paper the MPP will be determined using the teaching and learning based optimization algorithm applied on an ideal single-diode cell model in the process of design of a photovoltaic (PV) power plant for the dimensioning of all the applied equipment.*

***Streszczenie.** W systemach fotowoltaicznych zawsze stanowiło wyzwanie określenie metodologii obliczania maksymalnego punktu mocy (MPM) dla danego systemu, lokalizacji i warunków atmosferycznych. Dlatego też w użyciu jest wiele metod optymalizacji, a także różne prezentacje obwodów ogniw fotowoltaicznych. W tym artykule MPM zostanie określone przy użyciu algorytmu optymalizacji opartego na nauczaniu i uczeniu się, zastosowanego na idealnym modelu ogniwa jednodiodowego w procesie projektowania elektrowni fotowoltaicznej w celu wymiarowania całego zastosowanego sprzętu. (**Algorytm optymalizacji oparty na nauczaniu i uczeniu się jako narzędzie do wyznaczania maksymalnego punktu mocy dla dwustronnej fotowoltaiki**)*

Keywords: maximum power point determination, bifacial photovoltaic, teaching and learning based optimization algorithm.
Słowa kluczowe: wyznaczanie maksymalnego punktu mocy, fotowoltaika dwustronna, algorytm optymalizacji oparty na nauczaniu i uczeniu się.

Introduction

The increased need for electricity and the strategy for application of green, clean and renewable energy sources for production of electricity encouraged the governments, the power companies and investors to orient the electricity production towards renewable energy sources. The photovoltaics are one of those sources that have been installed in the world following an exponential rate during the years. The same applies in North Macedonia with a trend more bifacial photovoltaics (PV) to be in installed in the coming years. During the past several years, by the companies dealing with design and installation of PV system, it was found out that during the design process it was very important to know the maximum power point (MPP) of a given PV system for different weather conditions. This is especially important in the case of the design and configuration of the individual elements of the PV system. In order to achieve this goal, there is a need for a large number of calculations of the MPP for different solar irradiations at different seasons and temperatures. Beside those conditions the bifaciality of the PVs has to be taken into consideration. Actually, the bifaciality of the PVs at some weather conditions can cause significant increase of the output power if it is not taken into consideration during the design process of a given PV plant. In order to tackle this problem a good and reliable optimization algorithm for determining the maximum power at given weather conditions should be used in which all the necessary conditions and different combinations can be taken into account. In this paper, the teaching and learning based optimization algorithm is applied in the optimization process.

Teaching and learning based optimization algorithm

The optimization methods generally can be divided in two groups: deterministic and stochastic methods. On the other hand, the stochastic methods are grouped in two main groups: direct search methods and heuristic methods. Most of the heuristic methods belong to one big group of the methods called nature-based methods. This type of methods can be organized in four main groups: Evolutionary algorithms, swarm-based algorithms, natural sciences-based algorithms and human behaviour related methods. The investigated teaching and learning based optimization algorithm belongs to the human behaviour related group of optimization methods. In this group beside TLBO algorithm also Cooperative search, Football game inspired algorithm, Cultural evolution and many others belong. Teaching and learning based optimization algorithm (TLBOA) is a population-based metaheuristic optimization technique that simulates the environment of a classroom to optimize a given objective function and it was proposed by R.V. Rao et al. in 2011 [1]. This means that the method works on a set of members named teachers and learners and by using the metaheuristic approach which translated from Greek language means meta (beyond or high level and heuristic (greek - heuriskein or euriskein, to search). The algorithm simulates a classroom in which in the first stage the teacher puts his hard work and makes all the learners of the class to be educated. Then in the second stage the learners interact with themselves to further modify and improve their gained knowledge. In this optimization algorithm, a group of learners is considered as population and different subjects offered to the learners are considered as different design variables of the optimization problem and a learner's result is analogous to the 'fitness' value of the optimization problem. The best solution in the entire population is considered as the teacher. The design variables are actually the parameters involved in the objective function of the given optimization problem and the best solution is the best value of the objective function. The main advantage of this method in relation to the other methods is that this method has no parameters that tailor the search during the iterations. This means that there are no parameters that have to be defined prior to the search or there is no need for their value definition that will influence the quality of the search and solution. A presentation of the main steps of the algorithm in a form of a block diagram is shown in Figure 1. As mentioned previously in the teaching and learning based optimization algorithm there are two major stages, the so-called teaching and learning stage.

TLBO starts with randomly generated initial learners. The initial population can be considered as the uneducated students or learners or class. In this stage of the algorithm the learners learn through the teacher. During this phase a teacher tries to increase the mean result of the class in the subject taught by him or her depending on his or her capability. However, as the teacher is usually considered as a highly learned person who trains learners so that they can have better results, the best learner identified is considered by the algorithm as the teacher. After each searching phase, the replacement strategy is performed to keep the old learners or replace them with newly educated ones.

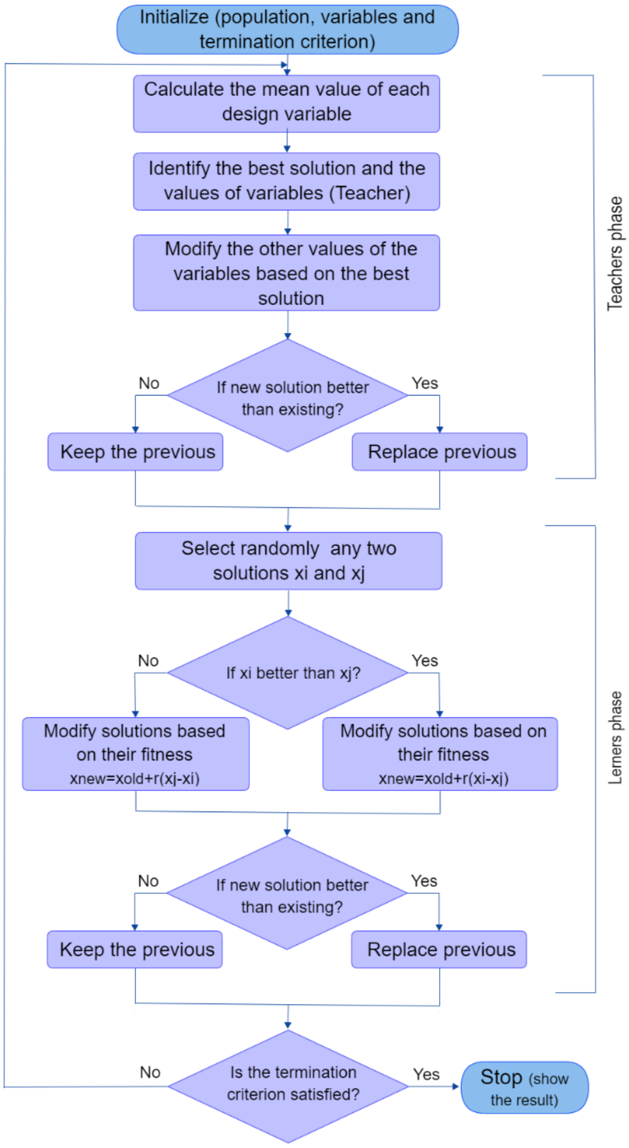

Fig. 1. Block diagram of the TLBOA

Maximum power point determination of a PV module using TLBOA

The objective of this research work is to determine the maximum power point of a bifacial photovoltaic (PV) module for different weather conditions. Therefore, in this work an ideal PV bifacial cell circuit presentation [2] is used in which the current through the diode is neglected. The standard mono-facial presentation is modified in order to take into account the bifaciality of the PV module which in this analysis is predefined to be 10%. The circuit presentation is shown in Fig. 2. The objective function for this optimization process is defined as absolute value of the difference between the calculated power ($P_{(mpp,TLBOA)}$) and the power given by the producer ($P_{(mpp,catalog)}$) for given conditions presented by equation (1).

$$(1)\quad Objective\ function = dP = \left|P_{mpp,TLBOA} - P_{mpp,catalog}\right|$$

Presentation of the photovoltaic cell model

In now a day there are many different models that are used to represent a PV cell. The most common types of models of solar cells that are used to model and define the cell are: single-diode, two-diode and three-diode cell model. Due to its simplicity of only three parameters the single-diode model is the most applied [3]. With some improvements of the single-diode model a new model can be defined that is consisted of five parameters (when the resistances are added). The two-diode model has seven parameters [4] and the tree-diode model has nine parameters [5].

When discussing different models of photovoltaic cells, by far the simplest approach is the ideal single-diode model, which is a model that consists only of two current sources in parallel representing the current generated from both sides of the PV module and a diode, where the output of the current source is directly proportional to the light falling on the cell. The diode is considered as an ideal diode with no current flowing through it. This model requires only three parameters to completely characterize the maximum power point, the current and voltage at the maximum power point, and the diode ideality factor [6]. Also, when researching about the optimization of bifacial photovoltaic modules and obtaining the maximum power point, the ideal single-diode model is more useful for optimisation due to its easier way to calculate the current generated from the front and rear side of the model, compared with the other methods. In this paper the single-diode model (in the paper presented as the ideal model) will be presented and used in the optimization process. In the text that follows the mathematical model of the ideal single-diode model is presented.

A. Ideal single-diode model

Photovoltaic cells in theory are presented with their single, double or triple diode presentation that contains a current source representing the current produced for different solar irradiation. Followed by a single, double or triple diode connected with a parallel and serial resistance that are covering the properties of the PV cell. In this investigation an ideal model will be used as presented in Fig. 2. It is a very basic straight forward model. It is defined with only two current sources that represent the two currents generated for certain solar insulation on the front and on the rear side of the module and an ideal diode. This model is good for fast calculations when there is not enough information about the PV cell and its equivalent circuit parameters necessary for the other more precise models.

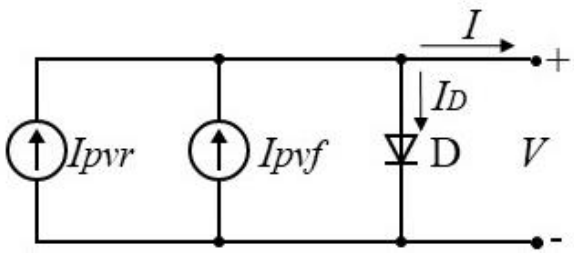

Fig. 2. Ideal bifacial PV cell model presentation

The values for the output current and the output voltage ared determined by using the following equations based on the equivalent circuit model taking into account the total number of cells per module. The output current of a bifacial solar cell can be represented by the total current *I* that is a sum of the current (I_f) generated by the absorbed light from the front, and the current (I_r) generated by the absorbed light from the rear [7]. The current of the solar cell tends to be proportional to the solar irradiation, the current of the front side of the module (I_f) is defined as:

(2) $$I_f = \frac{S_f}{G_{STC}} * I_{mpp}$$

where: S_f is the front irradiation of a bifacial solar cell and I_{mpp} is the current at the maximum power point generated under STC - Standard Test Conditions (1000 W/m^2, 25 °C, AM 1.5G) and G_{STC} is the solar irradiation at STC.

Bifaciality (Bifi) is one of the ways to differentiate the input solar irradiation between the front and rear of the module. Bifaciality can be expressed using the following equation in relation of the short-circuit currents ($I_{SC,f}$ - short-circuit current of the front under STC; $I_{SC,r}$ - short circuit current of the rear under STC) [7].

(3) $$Bifi_{I_{sc}} = \frac{I_{sc,r}}{I_{sc,f}}$$

Therefore, the current generated by the absorbed light of the rear side of the module can be expressed by the following equation:

(4) $$I_r = Bifi_{I_{sc}} * \frac{S_r}{G_{STC}} * I_{mpp}$$

Based on the PV cell model presentation shown in Fig. 2 and taking into account that the didode is considred as ideal, the total output current is defined as:

(5) $$I = I_f + I_r$$

The output voltage for a bifacial solar module can be determined using the equation shown below:

(6) $$V_{module} = V_{mpp} * \left(1 + \frac{\delta_{V_{oc}}\,(t-25\,°C)}{100}\right)$$

where: δ_{Voc} is the temperature coeficent for the voltage of the bifacial solar module. Based on the previously presented PV cell parameters the output power from the bifacial PV module can be determined by using the following equation:

(7) $$P_{mpp,TLBOA} = V_{module} * I$$

In the optimisation process the voltage V_{module} is additionaly multiplied by an optimisation parameter x that is varied between [0,1] in order to introduce the variable nature of the output voltage. The presented mathematical model of the bifacial PV module is implemented in the TLBOA in oreder to calculate the objective function of the optimization and determine the MPP for given weather conditions. In the text that follows an overview of the parameters of the investigated PV module are presented.

B. Parameters of the investigated PV module

The photovoltaic module that is investigated in this work is a bifacial PV module p-type named JAM72D30 540/MB. In Table 1 some of the data by the producer JA Solar are shown. The parameters are determined at standard test conditions (STC) such as: irradiance 1000 W/m^2, cell temperature 25 °C, air mass AM1.5G.

Table 1. Parameters of the investigated PV module

Parameter	Unit	Value
Peak power	(Wp)	540
Maximum voltage per MPP	(V)	41.64
Maximum current per MPP	(A)	12.97
Open circuit voltage	(V)	49.60
Short circuit current	(A)	13.86
Efficiency	(%)	20.9
Area of the module	(m^2)	2.58

Table 2 shows the characteristics of the investigated PV module, when bifaciality of 10% is taken into consideration. This data is also given by the producer and in more details is presented in reference [8].

Table 2. Parameters of the PV module with 10% bifaciality

Parameter	Unit	Value
Peak power	(Wp)	578
Maximum voltage per MPP	(V)	41.65
Maximum current per MPP	(A)	13.88
Open circuit voltage	(V)	49.93
Short circuit current	(A)	14.93

By analyzing the data in Table 1 and Table 2 it can be noticed that the increase of the output peak power for the bifacial PV in relation to the standard PV is due to the presence of the back side of the PV and its active involvement in the production of the output power. The influence of the back side of the bifacial module when active can be detected as an increase of the overall output current, compared to the current when only the front side of the module is active. In the analysis the values from Table 2 were included in the optimization process as input data and therefore, the back side of the module was also taken into consideration.

Optimization results from the TLBOA search

The optimisation of the objective function using teaching and learning based optimization algorithm was performed on the previously presented model of photovoltaic module. The optimisation was realised for few different solar irradiations starting from 200 W/m^2 up to 1000 W/m^2. The optimization of the objective function is realized for the presented simplified model and its equations, where the output voltage of the module is defined as an optimization variable. As mentioned previously, the objective function is defined as an absolute value of the power difference of the calculated maximum power by the TLBOA and the experimentally determined value given by the producer for certain conditions. The change of the value of the objective function during the iterations is presented in Fig. 3. In Table 3 the optimisation results for the simplified model for bifacial module for solar irradiation of 1000 W/m^2 in relation to the catalogue data are presented. In Table 4 and Table 5 the optimisation results for 600 and 200 W/m^2 in relation to the catalogue data are presented, respectively.

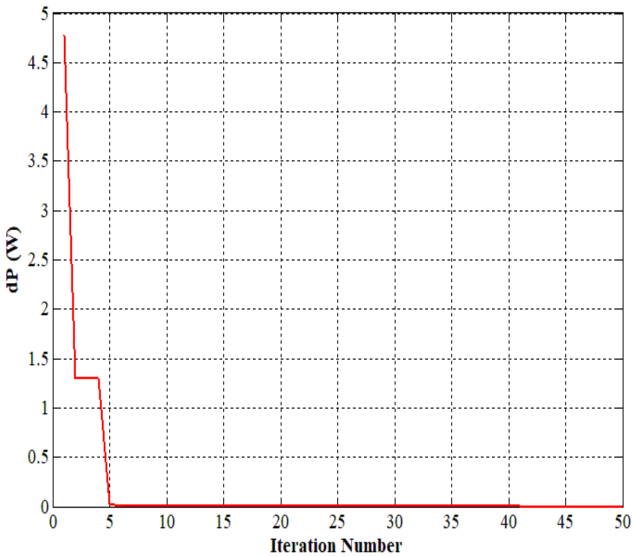

Fig. 3. Objective function change during iterations

Table 3. Optimisation data at 1000 W/m^2 and 20°C

Parameters	Unit	Catalogue data	TLBOA solution
V_{mpp}	(V)	41.65	41.2668
I_{mpp}	(A)	13.88	14.009
ΔP	(W)	/	$5.684 \cdot 10^{-13}$
P_{mpp}	(W)	578.102	578.102

Table 4. Optimisation data at 600 W/m^2 and 20°C

Parameters	Unit	Catalogue data	TLBOA solution
V_{mpp}	(V)	41.3	39.5006
I_{mpp}	(A)	7.526	8.4111
ΔP	(W)	/	$5.6843 \cdot 10^{-14}$
P_{mpp}	(W)	310.8238	310.8238

Table 5. Optimisation data at 200 W/m^2 and 20°C

Parameters	Unit	Catalogue data	TLBOA solution
V_{mpp}	(V)	40.16	39.51
I_{mpp}	(A)	2.75	2.795
ΔP	(W)	/	$1.4737 \cdot 10^{-11}$
P_{mpp}	(W)	110.44	110.44

Based on the results presented in Table 3, Table 4 and Table 5 it can be concluded that the TLBOA for the single-diode simplified model of photovoltaic modules gives quite good results for the objective function for all different presented solar radiations. It can also be noticed that the power difference is quite small for all analysed scenarios. Furthermore, it can be noticed that the estimated voltage value for the different presented scenarios is quite close to the voltage value given by the manufacturer for the different solar radiations.

Table 6. Comparative optimisation data at 1000 W/m^2 and 20°C

Methods	Parameters		
	V_{mpp}	I_{mpp}	P_{mpp}
	(V)	(A)	(W)
Catalogue data	41.65	13.88	578.102
TLBOA	41.2668	14.009	578.102
GA	41.362	13.977	578.115

In order to validate the results from the TLBOA search the same parameters are compared with the data gained from Genetic algorithm (GA) [9] search as presented in Table 6. The teaching and learning based optimisation algorithm shows good performance and a bit better results in relation to the GA and therefore can be successfully used for determining the maximum power point for given type of modules or whole power plant. The presented approach gives the possibility for fast and accurate results in the determination of the maximum power point for given PV modules and power plant, which is very important for the design process. This is a good starting point for further investigations in which wide range solar irradiations at different temperatures. In addition, different PV cell models can be investigated in relation to the presented one. Finally, also different optimisation can be implemented in order to test the quality of the search and solution of the presented TLBOA in relation to other nature-based algorithms such as gravitational search algorithm, multiverse search algorithm and others [10-11].

Conclusion

In this paper the authors are giving a brief presentation of a novel technique for optimisation that can be very successfully used in the determination of the maximum power point of PV cells, as well as modules. The optimisation method used for this purpose is named teaching and learning based optimisation algorithm. In the work this algorithm has been introduced and implemented. The power difference of the calculated power and the catalogue given one is selected as an objective function in the optimal design. The optimisation results from optimisation process are presented and analysed for different solar irradiations such as: 200 W/m^2, 400 W/m^2 and 1000 W/m^2 in relation to the catalogue given values by the producer. Based on the presented data it is evident that the optimized TLBOA solutions for different solar irradiations are better solutions in relation to the producer's data. As a future work additional optimizations will be performed using different PV cell model representations involving single, double and triple diode models. Furthermore, also different optimisation algorithms will be taken into account.

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